Socio-Spatial Comfort: Using Vision-based Analysis to Inform User-Centred Human-Building Interactions

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A well-designed workplace has a direct and significant impact on our work experiences and productivity. In this paper, we investigate how office interior layouts influence the way we socially experience office buildings. We extend the previous work that examined static social formations of office workers by looking at their dynamic movements during informal desk visiting interactions. With a month of video data collected in the office, we implemented a vision-based analysis system that enables us to examine how people occupy space in social contexts in relation to desk configurations. The results showed that both social territoriality and approach path highlight social comfort in human-building interactions, which are different from efficiency or path optimization. From these findings, we propose the concepts of socio-spatial comfort: *social buffers*, *privacy buffers*, and *varying proxemics* to inform a user-centered way of designing human building interactions and architecture.

CCS Concepts: • **Human-centered computing → Visualization techniques**; **Collaborative and social computing theory, concepts and paradigms**; *HCI theory, concepts and models.*

Additional Key Words and Phrases: socio-spatial comfort; social comfort; human building interaction; spatial analysis; skeletonization; proximity

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1 INTRODUCTION

The built environment has a significant influence on the experience that people have in buildings, leading to different types of space usage behaviours [7, 67, 93, 96]. For example, the structural configuration of a building adjusts the level of natural light at each area, leading to different experiences of indoor lighting. Also, interior elements such as furniture, walls, pillars and windows [69] influence the perception and use of space by the occupants resulting in different shapes of social formations.

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Considering that we spend more than 90% of our time inside buildings [35], it is important to incorporate the impact of interior elements on occupants when designing spaces as well as when designing interactive technologies for real or virtual environments [3, 103].

In the field of Human-Building Interaction (HBI) [3], Human Computer Interaction (HCI) and ubiquitous computing (Ubicomp), there have been several attempts to capture *architectural comfort* in-the-wild, and identify how those are related to structural elements in the architecture [4, 62, 75, 80, 88, 106]. The first wave of research investigated *physical comfort*, which describes how people perceive the environmental aspects of the building, such as *thermal comfort* [106], *visual comfort* [75] or *glare reduction* [51], and *air quality* or *respiratory comfort* [22, 60, 106]. A second wave of research started to investigate *psychological comfort* [28], which mainly describes how people are psychologically engaged with spaces; for instance, the preferred seating zones at hot docking office layouts [4] or aspects of comfort during travelling [6]. Both physical and psychological approaches were used as a basis for user-centered architecture/HBI design processes [3, 50], including evidence-based design [88, 90], occupancy simulation [31, 79] or pre-evaluation frameworks [4, 103]. Still, most are focused on the interactions of individuals, even though space is often occupied by multiple people leading to various social interactions.

Prior work in CSCW and social computing have investigated the relation between physical space and social interactions. Proxemics and F-formations have been the fundamental social theories that describe spatial positions, orientations, and spatial arrangements of people's bodies. Building upon this concept, a few efforts also uncovered that architectural elements (e.g., furniture, walls, etc.) have a large impact on the areas where occupants prefer to be during social contexts. This highlights the need for an additional concept or theory to illustrate how social comfort is related to physical space, which could help form a basis for the intersection between HBI and CSCW studies.

The goal of this paper is to bridge the notion of spatial and social comfort by proposing the concept of ***socio-spatial comfort*** to inform designers in creating user-centred human building interactions, along with novel visualizations and analytics. Inspired by Krogh et al. [61] who proposed the concept of socio-spatial literacy to describe physical space-dependent social behaviours, we define a new term, *socio-spatial comfort*, as the *psychological* aspect of the space that shapes comfortable social interactions, and we explore this concept using a large dataset collected in an office setting (Figure 2). While some existing studies in office contexts focused on socio-spatial interactions in common spaces (e.g., corridors, printing rooms, cafeteria), our study focuses on personal desk spaces, which can be perceived both as personal territory and as public space [46, 96]. Both the physical transition

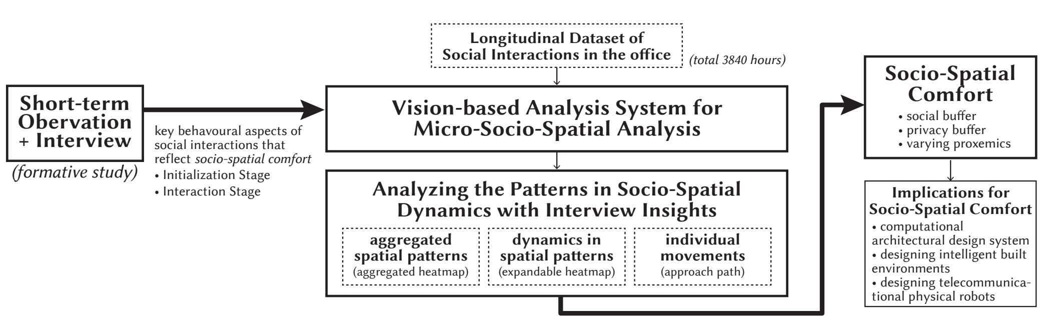

Fig. 1. Based on a formative study (left), we developed a vision based tool to analyze socio-spatial interactions (centre). Using this tool and a longitudinal dataset, we developed a set of concepts describing Socio-spatial Comfort (right).

between interstitial spaces and dedicated spaces, and the temporal change in status of a fixed space, have not been addressed in previous research despite the trend to increase employee density and to decrease dedicated desks for employees. For example, the use of hot desking [61, 89] has become common in offices. We argue that socio-spatial comfort could be an essential concept in the design of a comfortable experience for human building interactions. Understanding the key factors of these experiences can also support the adaptation of space layouts during times of physical distancing such as with the COVID-19 pandemic.

We started with a formative study by observing social interactions near personal desks and conducted follow-up interviews (Figure 1). The major insight was that socio-spatial comfort is a type of tacit knowledge [84] but can be captured by analyzing embodied interactions and by considering detailed kinematic movements over time. The way people socially occupy space was not based on efficiency. Instead, there are specific areas that people want to pass by or avoid altogether which are unique to each desk configuration.

We employed a computer-vision based approach and added a Socio-Spatial Analysis System to our existing Skeletonographer tool [69] to compute, analyze and visualize accurate spatial movements of people using video inputs (Figure 4). Whereas our previous tool just generated kinematic skeletons [21] of occupants from video sources, our new more advanced system can depict the computed footprint locations, projecting them on to a 2D floor plan. This approach can process a large behavioural dataset from a longitudinal study and then visualizes the patterns of social dynamics using various techniques such as aggregated heatmaps, expandable heatmaps, path-drawing and onion-skinning (Figure 5). These visualization approaches allow us to identify repeated spatial movements which were not available in our previous ethnographic study [69].

We then took a data-driven approach with a video dataset of 3840 hours (4 weeks) of interactions at various desk configurations in an office setting, and investigated socio-spatial comfort using our analytic system (Figure 1). The combination of the visualized results together with insights from the interviews we performed reveal that the continuous movement during social interactions contain rich insights in terms of preserving comfort, and the representation of these variations could inform future design solutions. We interpreted the observed patterns, and proposed three concepts to describe socio-spatial comfort: *social buffers*, *privacy buffers*, and *varying proxemics* 2. Based on these insights, we discuss the potential implications of the proposed concept for shaping human building interactions with a lens of socio-spatial comfort.

There are several limitations to this work. Psychological comfort was not explicitly collected from the occupants; instead, it was interpreted from the individual's space occupancy patterns

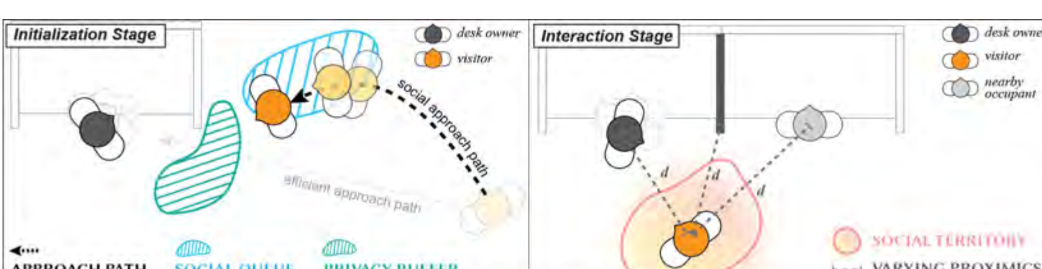

Fig. 2. We introduce the term Socio-Spatial Comfort which illustrates how spatial elements contribute to psychological comfort during social interactions. Three concepts are proposed to explain socio-spatial comfort: *social buffers*, *privacy buffers*, and *varying proxemics*.

collected over time. Also, our study only took into account the dataset collected in an office, even though the concept of socio-spatial comfort could apply to other contexts such as hospitals, libraries, or museums. Still, we believe that our proposed concept, together with the accompanying open dataset, establishes a novel way of considering comfortable socio-spatial interactions, not only by informing computational space design systems, but also active intelligent building environments. With the ongoing progress of the ubiquitous computing vision [107], taken together with pervasive and intelligent systems inside spaces, new human-robot interactions can also be considered. Devices such as collaborative robots, adjustable displays, and mobile telepresence robots are beginning to move into light manufacturing and office environments and these devices also need to be aware of socio-spatial comfort to be active participants in creating comfortable social experiences.

This paper makes four contributions. First, we introduce the term, *socio-spatial comfort* and propose three concepts to describe this notion using real-world datasets. Second, we propose a vision-based occupancy analysis system that supports analyzing social dynamics using kinematic skeletons and four spatio-temporal visualization techniques. Third, based on the results, we discuss the implications of socio-spatial comfort in designing user-centred human building interactions. Lastly, we open source our analyzed footstep dataset with this paper so that future researchers can use it to apply and extend socio-spatial comfort analysis in their projects (see Appendix A.3 & Figure 14).

2 RELATED WORK

Our research builds on existing work on understanding experiences in architectural space design with respect to *socio-spatial comfort*. We reviewed four related topics: 1) environmental and psychological comfort in architecture, 2) the influence of physical space on social interactions, 3) methodological approaches for analyzing socio-spatial behaviours, and 4) designing for comfortable human building interactions

2.1 Physical and Psychological Comfort in Architecture

For decades, in the architectural domain, there have been efforts to understand the correlation between architectural and human experience as a goal of designing human-centric and sustainable architecture [7, 46, 50, 93, 96]. The environmental qualities of buildings have been evaluated, through metrics such as thermal [106], visual [75], lighting [51], and acoustic [16] comfort.

In recent works in HBI, the definition of architectural comfort has been extended by considering *psychological factors*, and researchers started to look into how the space configurations influence the way people perceive the space, and how these psychological perceptions shape space occupancy patterns. Alavi et al. [4] found that the *visual openness* of an area influenced the comfort within an office environment. In our previous study, we took a similar approach with social contexts and identified that space configurations influence the way people comfortably orient and position themselves to each other [69]. However, as it was an ethnographic study, we were not able to analyze long-term data immediately, making it difficult to generalize the core reasoning on how the space design influences social comfort. In this paper, we build upon our previous work and propose a new concept called *socio-spatial comfort*. As we added a new technique to analyze and visualize spatial behaviours computationally, we can now illustrate how physical spaces could encourage or discourage social interactions.

2.2 Physical Space on Socio-Spatial Interactions

Researchers from multiple disciplines, such as architecture, sociology, and environmental behaviour have tried to understand the relation between physical space layouts and social behaviours [7, 46, 93, 96]. The paradigm of *evidence-based architectural design* [88, 90] accelerated the collection of empirical data in existing buildings and we discern between two main research approaches for understanding socio-spatial correlation that we call the *macro-perspective* and the *micro-perspective*.

The *macro-perspective* is based on statistical analysis using the frequency of interactions in relation to physical environments [5, 17–19, 30]. For example, levels of communication and creativity increased in an open layout [5, 18], in printing rooms and kitchens [19, 30] as well as in workstation areas [85, 89]. However, these approaches do not reveal how spaces are socially occupied and how people socially perceive the physical space.

On the other hand, instead of aggregate quantities, the *micro-perspective* examines behaviours between individuals, such as spatial distance [46], positions [100], and arrangements [58, 74]. The foundational theory in social science is *Proxemics* theory [46] that describes comfortable spatial zones during collocated social interactions: *intimate* (0–0.45 m), *personal* (0.45–1.22 m), *social* (1.22–3.66 m), and *public* (>3.66 m) zones. Kendon's *F-formation* theory is often combined with proxemics when describing the range of spatial patterns of group formations [58, 59]. Later research took spatial elements into account and identify how the physical spaces and devices influence frequently observed social arrangements (e.g., tourist information center table [74], a hospital table [100], display angles [54], and desk configurations [69]). In short, space design and object placement both have a strong impact on the detailed micro-spatial behaviour and occupant experiences inside buildings.

While most of the related work from the micro-perspective considers the *static* use of physical space (e.g., F-formations [58], proximity [46]), our formative study identifies that socio-spatial comfort should be a *dynamic* concept, and understanding how people socially occupy the space over time is significant. Krogh et al. [61] explained these behavioural dynamics using three concepts *proxemic malleability*, *proxemic gravity*, and *proxemic threshold* (e.g., groups leaning towards the camera during the conference call, poses gravitating towards workstations, etc.); however, they did not uncover micro-specific spatial patterns (e.g., zones, positions, paths). Inspired by this work, we build upon the micro-perspective approach by looking at dynamic spatial movements during social interactions in relation to spatial elements. We proposed a set of concepts to demonstrate spatial dynamics, *social buffer*, *privacy buffer*, and *varying proxemics* (Figure 2). Different from previous theories, our proposed concepts are space-oriented, and describe how the proxemic distance can vary due to architectural elements. It illustrates how preferred social distances are dynamic with respect to the space layout and devices (e.g., monitor), which leads to the formation of geometric shapes rather than (single value) distances.

2.3 Systematic Approaches for Analyzing Socio-Spatial Behaviours in-the-wild

Analyzing behaviours of how people interact with each other and their surroundings [56] can provide rich empirical insights. In social contexts, analyzing physical *distances*, *orientations* and *postures* has been a major approach inspired by Kendon's F-formations [58] and Hall's proxemics theory [46]. Researchers have also developed digital ethnographic approaches [97] to understand socio-spatial behaviours; however, observing behaviours from raw video was time-consuming and could not provide accurate details of embodied aspects of people in relation to the physical environment.

2.3.1 Sensing Socio-Spatial Interaction Properties. To increase the scalability and efficiency of analysis, pervasive sensors have been applied to overcome the limitation of video analysis by automatically capturing social interactions from the raw datasets and correlating the data with spatial information. Wearable devices (Bluetooth wrist-bands [9, 103], Zigbee-based indoor locators [109], or RFID badges [19]) are often used to detect social interaction moments while preserving visual privacy. However, they could only detect the frequency and the duration of the interaction and they do not collect accurate movements or positions of the occupants, which are important aspects in terms of social comfort [46, 96]. Alternatively, the Proximity Toolkit (infrared sensors) [72], EagleView (depth sensors) [110], and Skeletonographer (vision-based skeleton generation) [70] techniques were proposed to capture rich embodied aspects of social interactions, such as poses or social distances. While these systems move us closer to extracting accurate micro-perspective socio-spatial patterns in relation to physical layouts or furniture, there is still a gap in the needed metrics and analytics.

To overcome these limitations, we propose novel extensions to a vision-based video analysis system that supports accurate spatial analysis while not losing detailed behavioural information. Based upon our previous work [69], our system automatically generates kinematic skeletons from the collected videos for anonymity and has been extended to provide more advanced analysis. We added spatial tracking to the kinematic skeletons, giving each a consistent id, and calibrated the position of each skeleton in 3d and over 2D floor plans. This allows us to spatially analyze accurate positions of occupants and align them with detailed social behaviours and surrounding spatial layouts. The computer-vision basis of the system scales and works well even on extremely large datasets.

2.3.2 Annotating Videos for Socio-Spatial Analysis. In addition to pervasive sensing, a large body of work in HCI has investigated video analysis interfaces to support researchers in analyzing longitudinal datasets efficiently. Inspired by Vcode [44] which identified the efficiency of synchronized video playback and a timeline-based annotation interface, similar techniques were applied and tested in various research fields including behavioural studies [20, 34], multimedia analysis [49, 64, 65] or learning contexts [23, 26]. However, this approach is still insufficient for analyzing the behaviour of specific objects or people in the scene (e.g., trajectories, territories, movements, etc.). This is especially important as the video collected in-the-wild includes elements that are not the target of the research. To overcome this problem, additional features were introduced, such as adding free-form drawings [113], bounding boxes [13, 63], or manual trajectory drawings [33, 34].

Our analysis system builds on these existing video analysis interfaces in terms of providing custom labels and visualizing the annotations in a timeline panel. However, compared to previous tools, our system automatically generates kinematic skeletons and their unique ID for each individual in the scene. Therefore, the users do not need to manually specify the regions for the annotation, which increases the user's efficiency in annotating complex social behaviours needed for analysis.

2.3.3 Visualizing Spatial-Temporal Patterns. Spatial-temporal visualization has been investigated in the field of HCI and Information Visualization to represent events or movements in space and time [34, 57, 81, 83]. 2D-based trajectory representations are often used in sports and architecture analysis. For example, several systems [81, 83] visualize the 2D trajectories of baseballs and players, based on the video data, for summarizing and logging purposes. Shapiro et al. [95] introduced a method called interaction geography that represents people's interaction events as a graphical form using space and time axes.

However, when it comes to longitudinal datasets, overlapping multiple trajectories can be difficult to interpret. A heatmap visualization is a common technique in spatial analysis to represent areas that are frequently occupied (hot spots) [4, 20, 91, 105]; however, this is at the cost of conveying temporal dynamics within the dataset. Therefore, several multi-dimensional representations have been proposed. The concept of a *space-time cube* [11, 32, 45, 57, 82, 101] was introduced in which the x and y axes represent the spatial information while using another dimension (e.g., the z-axis) to represent time. Inspired by these systems, we implemented four types of spatial-temporal data visualization techniques for socio-spatial studies. In addition to heatmaps and path drawings, we implemented a hybrid expandable heatmap which describes dynamics among smaller aggregated windows of time. Lastly, we developed a pose onion-skinning visualization to alternate between a perspective skeleton view and a 2D position view.

2.4 Designing for Socially Comfortable Human Building Interactions

In architectural space planning, the evaluation of the spatial experience is mostly done in two ways: *space syntax* and *occupant simulation* with agency. First, *space syntax* [50] is a collection of methods that quantitatively analyze the physical characteristics of a space. Most previous works have been based on the topology of spaces to drive efficient computational processes [86]. The *visibility graph* [102] took this further to convey visual comfort in relation to space. We build upon this concept to evaluate socio-spatial comfort in space design. Also Edward Hall [46] proposed the concept of proxemics, defining a set of static interpersonal distances for comfortable social interactions. While these guidelines are helpful they do not consider physical barriers and furniture, nor do they describe dynamic motions. Using the collected data in the wild, we aim to reveal spaces that are perceived as socially comfortable over time in relation to given desk setups.

Another way to evaluate scenarios in architectural layouts is with occupant simulation. A well-known example is evacuation crowd simulation [43] to confirm the safety of the building. To generate realistic occupant behaviours, researchers trained their occupant model using real world data [8, 36, 52]. However, the majority of this work uses path finding algorithms or optimization and ignores the micro behaviours of occupants. The observations from our formative study also indicated that detailed real-life behaviours are not yet reflected in mathematics-based simulation. To understand space occupancy that reflects socio-spatial comfort, we believe that additional data and concepts are needed.

3 FORMATIVE STUDY

We started with a lightweight formative study to determine if there are specific areas or zones that contribute to social comfort within an office setting, and if so, to explore how we can capture these areas. As described in the Introduction, we focused on informal social interactions near personal desk areas. Although this aspect has not been addressed in previous works, we argue that considering socio-spatial comfort during informal meetings at personal desks is significant for two reasons. First, its complexity in having dual roles as personal territory and social zones increases the sensitivity of occupants to social comfort, and second, due to the common use of open desk areas in the office. To answer the research questions, we conducted an observational study along with follow-up interviews [114] in the office setting. The results revealed that people's physical movements during social interactions are not based on efficiency; instead, their dynamic movements unconsciously reflect *socio-spatial comfort.* These findings inspired us to develop novel analytics and techniques for our next step.

3.1 Study Environment: the Office

The *in-the-wild* field observation was conducted in one section of an office building (100 ft x 70 ft), which is occupied by a global software company located in North America, as shown in Figure 3. The employees are from multicultural backgrounds including US, Canada, France, India, China and Korea, with a flat hierarchy working culture. Personal desks are assigned to each of them with various setups. Some desks are cabin-style and surrounded by walls while others are arranged as an open desk setup with different arrangements based on the spatial restrictions (e.g., columns). The partitions were optional desk accessories, so some desks have partitions while others do not. For every desk, a 22-inch monitor is installed so that employees can connect with either a workstation computer or their laptop.

3.2 Procedure

3.2.1 Field Observation & the 1st Analysis. The social interactions that occurred near the personal desks in the office were observed for eight hours, over two days. Due to privacy issues, we took the same approach as Azad et al. [10] and performed the real-time observation on the spot without any digital recordings. The observer's location is marked by a star in Figure 3. As the observer was one of the employees and aquainted with the other occupants, she was able to observe people's natural behaviours in the office without causing any interruptions. The observer watched the general office area; and when someone seemed to approach other's desks, their spatial behaviours were logged, including how they approached, and how they moved around during the social interactions. To efficiently and manually collect these behaviours without any video capture, we took a similar approach as Krogh et al. [61]. We printed the 2D floor-plan of the office in advance and abstractly sketched people's socio-spatial behaviours. Next to the drawings, we highlighted the real-time insights that we gained from each instance as text. When the observation phase was complete, we categorized our sketches and identified a set of interesting socio-spatial behaviours (early clusters) which seem to be aligned with *socio-spatial comfort*.

3.2.2 Contextual Interview & the 2nd Analysis. We then interviewed six employees who were involved in more than 30 social interactions. We started the interview by asking them to specify the areas that they tended to occupy to preserve social comfort during their interactions near desks. Although all participants indicated that they cared about social comfort while locating themselves, none of them clearly remembered how they physically occupy the space. Therefore, we shared our sketches and discussed how psychological aspects may have influenced their spatial behaviours. The results were analyzed using thematic analysis [40] using early clusters as a basis.

3.3 Results

In total, we collected 132 cases of informal social interactions that occurred near personal desks. For 117 of the occurrences, the cases were accompanied by spatial movements (e.g., walking or approaching), and the rest were the interactions between people sitting next to each other without any positional movements (e.g., turning their head to chat). Seating arrangements were not based on project teams or relationships between colleagues.

We clarify that our analysis focused on the former group as our research focus is on spatial aspects of social interactions and their dynamics. Borrowing terminology from Sailer et al. [89], we named these as *visiting interactions* and define it as 'social interactions that happened at one's desk due to someone visiting.' Consequently, for the rest of the paper, we also use the terms *desk owner*, and *visitor* to distinguish people involved in the interaction. The observed visiting interactions were composed of three types: the person purposely visiting or approached the colleague's desk, a person randomly visiting the colleague's desk in the middle of travelling, and a person sitting at a desk *recruits* someone who is passing by to visit.

The qualitative interviews confirmed that our initial set of proposed socio-spatial behaviours, gathered from the observations, suggests an unconscious intention to maximize social comfort. In contrast to previous works that focused on *interaction moments* [69, 96], our findings showed that behaviours for *initializing* the social interaction also have a significant influence on social comfort. Therefore, we categorized our findings into two main stages: an *initialization* stage and an *interaction* stage.

3.3.1 Initialization Stage. This stage indicates the period in which one or more people visit another person's desk triggering a social interaction. Whereas Gronbaek [38] studied observed behaviours for initiating informal social interactions near personal desks (e.g., adapting poses around the

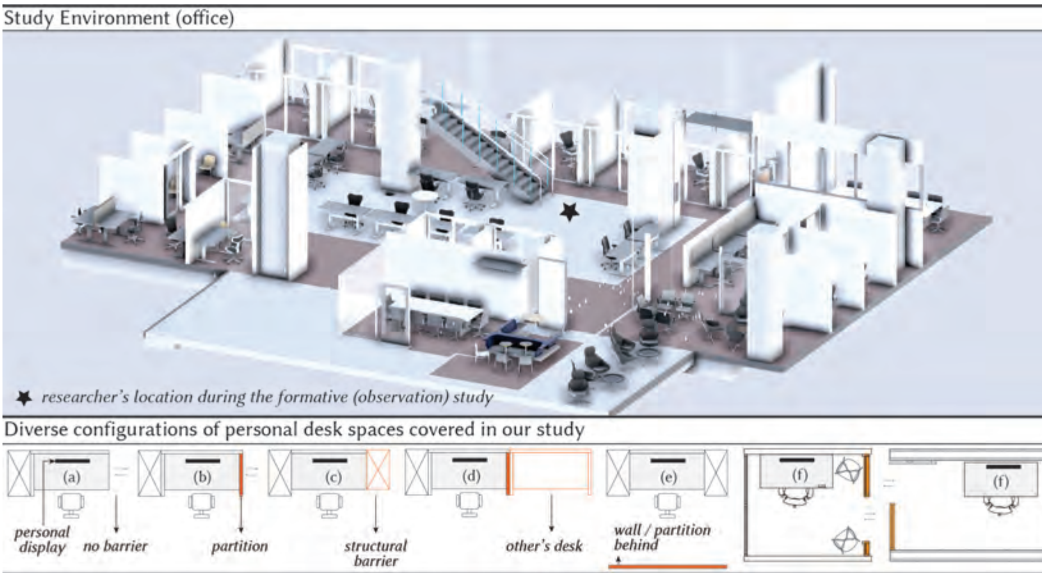

Fig. 3. A rendering of the study environment where video was collected in the office (top). In addition, we compare interactions with various desk configurations (a-h).

display, height shifting the desks), our study focuses on how people approach someone's desk, which also has a significant impact on their comfort. The occupants did not always take an efficient path in terms of walking distance; instead, they often detoured around the space. All interviewees highlighted that these movements were intentional to avoid interrupting desk owners as well as to give them some time to be ready for the upcoming social interaction. However, all the participants had difficulty in recalling and verbally describing the exact paths they took. As moving paths drawn by human observers (researchers) were not accurate enough, it was challenging to extract detailed spatial influences on social comfort with the sketching method.

Still, based on our brief observation sketches, we found that different desk configurations seemed to induce different approach strategies. When the side of a desk is open, people tended to approach from that side of the desk, and paused at a certain distance until the desk owner's attention was caught. When there were barriers (e.g., other desks, walls) on both sides of the desks, people had no choice but to approach from behind the desk owners along paths of various curvature. In this case, the occupants tended to move backwards as soon as the desk owner noticed them. From the interview, we realized that the position where the visitor and the desk owner made *eye contact* implies several meanings in terms of social comfort. We observed that the visitors tended to pause in the middle of an approach and waited until the desk owner looked back at them. This was not only to kindly inform the desk owners about the visit, but also for the visitors to be confident about their visit. In cases where the desk owners were too concentrated on their work or wearing earphones and did not recognize the visitor's first approach attempt, the visitors made additional attempts to catch the desk owner's attention. Some approached from the side to get the owner's attention and then stepped back afterwards, while others waved their arms while maintaining the same distance.

3.3.2 *Interaction Stage.*

Similar to the findings from other related works [69, 96], we also found that how people occupy the space during social interactions also reflects social comfort, and depends on the desk configurations. Visitors kept a certain distance from the desk to avoid intruding in a personal area. Visitors stood diagonally behind or beside the desk owner, who rotated the chair towards the visitor. If that formation was impossible due to the physical environment, the visitor seemed to keep a larger distance from the desk. However, the exact distance difference could not be measured from our study setup. When there were walls or pieces of furniture near the desk, the visitor tended to stay near them.

The key finding was that, whereas most of the prior work focused on analyzing static formations in relation to spatial elements [69, 74, 96], we observed the position and the arrangement of the visitors changed dynamically over time throughout the interactions. Four interviewees highlighted that it was an unconscious behaviour to move around the space while interacting with people, and they were not aware of their dynamic movements until we highlighted it. One participant described it as a type of prototyping process to figure out where to stand so that they can stay at a particular position for a more extended period once they feel comfortable.

3.4 Discussion

The formative study revealed that the occupants' spatial movements play a significant role in shaping comfortable social interactions. The way people socially occupy spaces were often motivated differently from *efficiency* or *space optimization*; instead, there are specific areas that they try to pass or avoid, which acts as fundamental knowledge to formulate the concept of *socio-spatial comfort*. When they *initiate* interactions, they approached a desk with a different path so as not to invade *personal territory* too suddenly [96]. Likewise, *during* social interactions, personal desk areas commonly turned into temporary social spaces by visits from co-workers, so visitors carefully choose their positions to maximize their comfort based on the given physical layout setting. In both interactions, their spatial arrangements changed over time, and they stayed longer at the positions where they felt comfortable.

These results warrant further examination of socio-spatial comfort with respect to physical space layouts. The formative study provided four important lessons for our next study. First, socio-spatial comfort is a type of tacit knowledge [84] aligned with embodied interactions and may involve unconscious movements. Therefore, it will be valuable to collect spatial movements of occupants in-the-wild with their normal setting. Second, the observational study could not provide accurate spatial positions of occupants concerning physical spaces or furniture items. Therefore, a more advanced method needs to be applied to collect detailed spatial arrangements and motions of each occupant for better pattern recognition and comparison. Third, the results highlighted the importance of considering dynamics in spatial movements during social interactions, both in the initialization stage and interaction stage. Therefore, different from the prior work that collected sketches of a single static instance [10, 69, 74], we need to take into account temporal aspects and record the amount of time people stayed at a particular position. Finally, we also need visualization tools to represent patterns from a longitudinal dataset that has both spatial and temporal aspects.

4 A VISION-BASED SOCIO-SPATIAL ANALYSIS SYSTEM

Due to the limited information that could be gathered from our formative study, we build on the computer-vision based ethnographic methodology pioneered in [69] to enable micro-perspective space analysis from video inputs. Our intention was to accurately capture and visualize detailed spatial movements using the dataset collected in-the-wild, so that we can formulate the concept of socio-spatial comfort using real-life evidences. We extend our Skeletonographer tool [70] and analysis process in four ways (Figure 4). First, our system automatically calculates occupants'

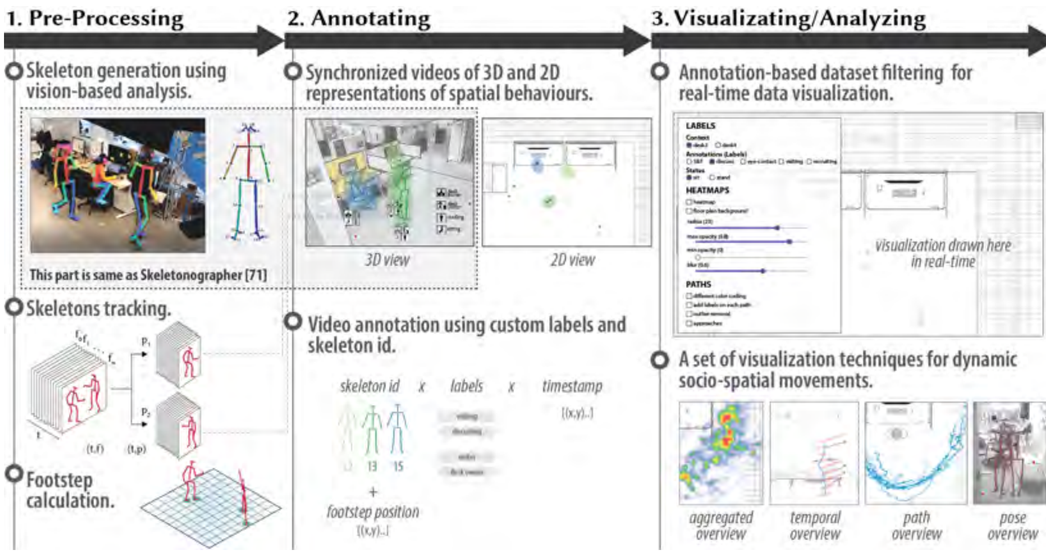

Fig. 4. The analysis process consists of three steps. To anonymize the video footage, we first generate kinematic skeletons using OpenPose and project occupant's footprints on a 2D floor plan. In a second step we annotate metadata e.g. labelling owner or visitor, waiting or discussing etc. In step three. we generate visualizations and analyze the data.

spatial locations from the video and generates 2D coordinates in relation to a 2D floor plan. It enables users to aggregate spatial patterns across many instances. The calculated positions were also correlated with physical environments such as desks or walls, which enables detailed spatial analysis. Second, the system lets users specify the target person (kinematic skeleton) in the video scene not only when applying custom annotations but also when visualizing the data. This is especially important for socio-spatial studies (e.g., only show the visitor's movements and ignore others in the scene). Third, by adding skeleton tracking, our system automatically recognizes the same person across video frames, enabling users to explore the dynamic aspects of socio-spatial movements easily. Lastly, the system supports four ways of visualizing the dataset based on the custom annotation filters. From heatmaps to pose onion skinning, our system can help researchers understand spatial-temporal information with both micro and macro perspectives.

4.1 Video Pre-processing

Using the given video input, our system generated skeletons by taking the same approach introduced in Skeletonographer [70]. We used 25 key points from the *OpenPose* library [21], as depicted in Figure 4, step 1. However, different from Lee et al. [70], we applied two additional steps to our system for achieving accurate analysis by tracking the skeletons and projecting footsteps on to a 2D floor plan.

We implemented a stable and consistent identifier between frames to analyze space occupancy for specific activities or interaction phases (e.g., the initialization period). As skeleton features can vary between poses and in relation to the camera, we obtained this identifier by tracking an individual's head. Using the head keypoints, our system tracked the head forward and backward during consecutive frame sequences. When the system loses head detection over certain frames, we have two frames with the head separated by a series of frames without the head detected. To prevent this discontinuity from resulting in a different identifier, we perform matching between the discontinuity. We use the heads found at the boundary of each discontinuity and use a distance threshold for matching. The distance depends on both the amount of time and a physical distance as described in [104].

Then, the system projected the occupants' footsteps to the 2D architectural layout by using measured and marked points in physical locations. These points were captured in the camera's perspective view and mapped to their locations on the 2D layout. Using *homographic* techniques, we are able to translate the skeleton's feet in the perspective view to their location on the 2D floor plan. This allows us to further understand micro spatial positions and movements in relation to a given setup. The computational jobs were synchronized across multiple computers using Amazon's Simple Queue Service, and JSON files corresponding to each video frame were generated, containing key joint positions, skeleton id, and timestamps.

4.2 Annotating with Skeleton Identifier

Our system provides an annotation interface similar to other video analysis tools [20, 44, 70]. To help users analyze socio-spatial comfort for each occupant in relation to 2D coordinates, two novel UI features were added: a 2D floor representation, and individual skeleton annotation (Figure 4). We used a custom Node.js server and the tool was written in TypeScript and HTML.

As shown in Figure 4, step 2, our system provides synchronized representations of a 3D perspective view (skeletonized videos) and a 2D View (top-down view). The system represents the occupant's footprints on the 2D floor plan and users can play back the motion of skeletons and 2D footprints by scrubbing the timeline bar. This 2D floor panel helps users understand the precise location of occupants, which is difficult in a perspective view.

Another feature we added is a video annotation tool. By clicking the custom labels, prepared in advance, users can quickly label phases and people. Different from Skeletonographer [69], our system provides a unique identifier to each skeleton as shown in Figure 4, step 2, bottom. This enables users to add annotations to a specific skeleton that they want to analyze, which is especially helpful when analyzing social behaviours. For example, if users highlight skeletons before clicking the label, the corresponding skeleton ID is automatically saved together with the annotation data. Moreover, in case users need to annotate each person's status (e.g., *desk owner* vs. *visitor*), the system can add label buttons whenever it generates a new skeleton (Figure 4, step 2, black icons in 3D view), so that they can apply the corresponding label to the context. As skeletons are tracked between frames automatically, users just need to add labels once whenever the occupant appears in the video. All the annotated outputs (skeleton ID, occupant types, activity labels, target desk) are saved as a JSON file with the corresponding video timestamp (starting and ending time), and are visualized on the timeline panel.

4.3 Visualizing Socio-Spatial Dynamics

Our system provides a visualization interface that helps users look at the collected socio-spatial movements and behaviours based on their custom annotations, to gain better insights (see Figure 5). We were inspired by visualizations introduced in EagleView [20] and GIAnT [105] that visualize hotspots, and paths. Whereas these works focused on visualizing interactions between people and devices (displays), we argue that our work extend these by focusing on interactions with other people and building layouts. As the formative study highlighted the importance in analyzing *dynamics* in socio-spatial movements, we tried to consider not only *spatial* but also *temporal* aspects of our longitudinal data. We implemented four types of visualization techniques: (a) aggregated overview, (b) temporal overview, (c) path overview, and (d) pose overview, each of which provide

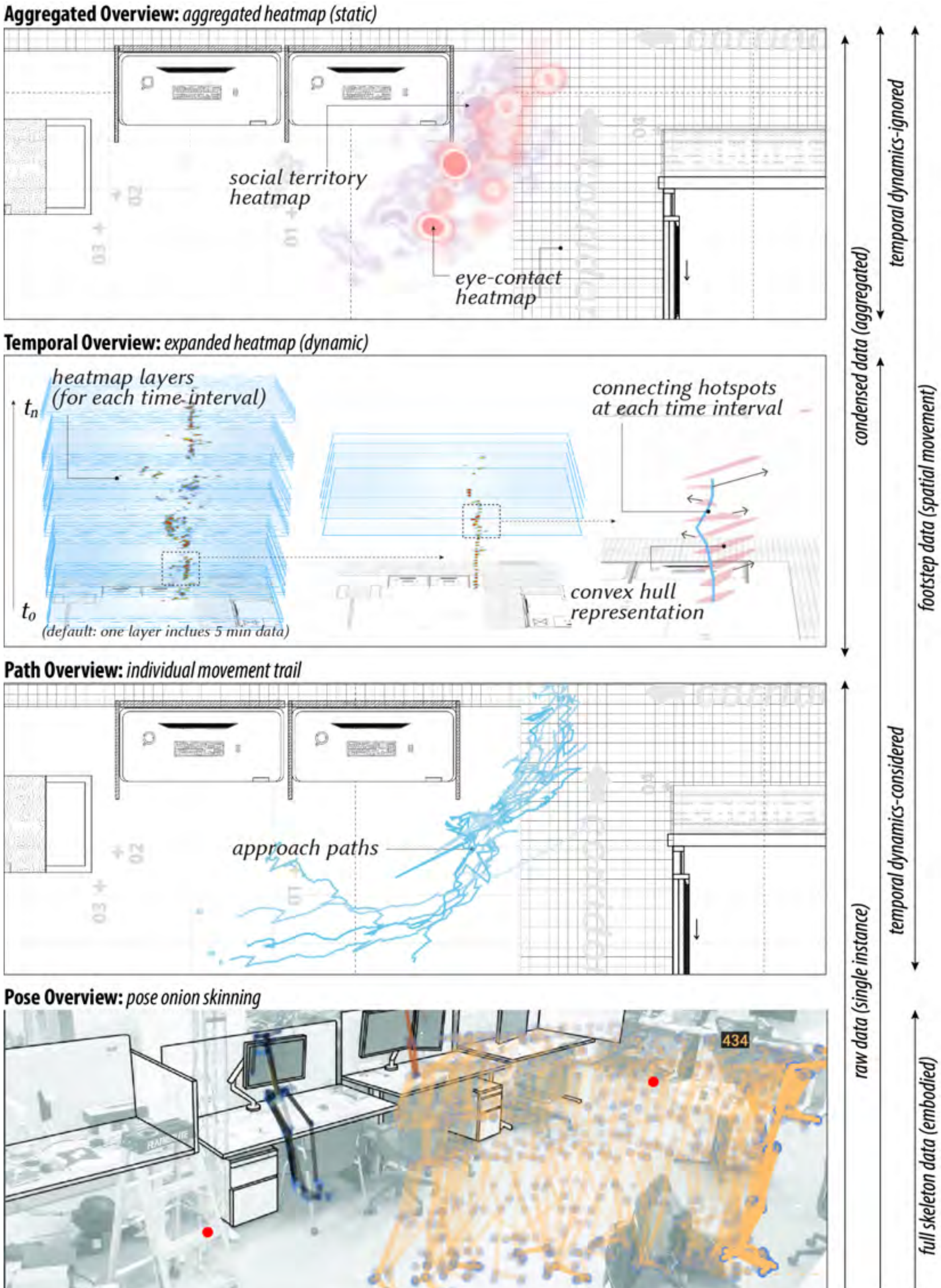

Fig. 5. The four visualizations generated by the system. The aggregated overview visualizes color-coded heatmaps of space occupancy. The Temporal overview allows to zoom in on specific time intervals. The path overviews displays all approach paths. The Pose overview, visualizes poses over time using an onion-skinning technique based on timestamp data.

different insights. We believe that interactions between these visualizations could support checking single behaviours (at a certain moment) as well as the integrated patterns (during a certain period).

4.3.1 Aggregated overview: aggregated heatmap. Similar to the prior tools that show the movement of people in a bird's eye perspective [20, 105], we implemented an aggregated heatmap on 2D floor plans and displayed the regions that each person occupied over time (Figure 5-a). Different colour codes were used for the dwell time of users. In the visualization UI panel, users can select labels generating custom heatmaps of occupants in a specific context (e.g., heatmap for visitors having a discussion at desk #3). In our case, this technique was helpful for demonstrating an overview of hot spots and territoriality of each social behaviour, such as making eye-contact or having a discussion. But the aggregated heatmap does not describe how each hot spot was occupied and ignores dynamic aspects of spatial movements.

4.3.2 Temporal overview: expanded heatmap. To overcome the limitation of an aggregated heatmap, we implemented *expanded heatmap* to highlight the temporal dynamics of collected data, as shown in Figure 5-b. The y-axis dimension represents a timeline (t_0 - t_n), and each stacked layer indicates a certain time interval. The system automatically generates multiple layers of heatmaps for each time interval. Based on the parameter input from the UI panel, the system modifies the visualization into a simplified version. One method draws the social territory using a convex hull algorithm, representing the shapes of space occupied at each time interval (Figure 5-b, pink shapes). Another method is to draw a line by connecting the hot spots at each time interval (Figure 5-b, blue line). Users can expand, zoom in, and rotate the stack of layers by scrolling and dragging the model with the mouse. Also, users can customize the length of each time interval and the spacing between layers from the UI panel. This technique describes the overview of dynamic spatial movements regardless of the size of the dataset.

4.3.3 Path overview: individual movement trail. In addition to the heatmaps, the system also visualizes the trail of each occupant's movements as paths (Figure 5-c). When drawing the approach lines, a central point between the skeleton's two feet are connected between consecutive frames to create a line. The central point is used for a smooth visualization. Also, we calculated each point's z-score before drawing the line to remove outliers. The system visualizes all the paths at once with the same label, but using the visualization UI panel (Figure 4, step 3), users can keep track of each path. This technique is important for analyzing physical movements that last for short periods of time, for example, the initialization stage of social interactions. The lines visually represent how the occupants approach the desk at a given space, which was found to have implicit meanings in terms of social comfort from our formative study.

4.3.4 Pose overview: onion-skinning. To take advantage of having embodied information aligning with footstep data, we implemented an additional visualization method to show pose transitions at a given timestamp (Figure 5-d). This method represents multiple frames of skeletons at once by tuning the opacity of each frame. This method could be useful when users want to look at the detailed embodied interactions of the selected time period to glance at the reason behind observed spatial movements.

5 VISION-BASED STUDY

As our next step, we applied the system described above to analyze micro-space occupancy patterns during social interactions at various personal desks setups. We started with the two-week video dataset introduced in [69]. Then we added another two weeks of video capture to identify the repeated patterns in socio-spatial movements, totalling four weeks of video of office interactions. Whereas Lee et al. [69] focused on analyzing multiple cases of how people orient and position

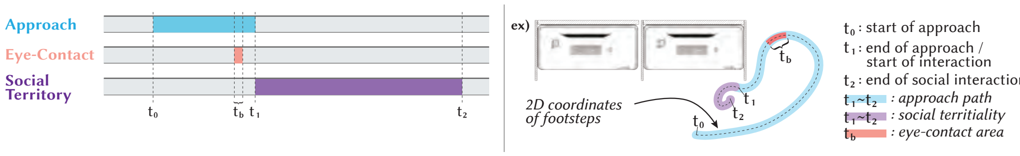

Fig. 6. We labelled approach, eye-contact and social interaction. Based on these annotations heatmaps and paths are generated.

themselves by watching skeletonized representations of the videos, we did not only analyze the data during the social interactions, but also covered approaching activities during the initialization stage, as indicated in the formative study. In addition, by applying our analysis system, we automatically calculate the precise physical positions and movements in relation to the 2D floor plan, and visualize the patterns with temporal aspects to better understand socio-spatial comfort.

5.1 Dataset

The data collection method as well as ethical review process were identical to the dataset described by Lee et al. [69]. The dataset was recorded with 24 RaspberryPi 3 single-board computers, each equipped with RaspberryPi Camera 2 modules and were installed throughout the office space. Videos were captured from 9:00 am to 5:00 pm for four weeks, between February 21th and March 30th 2019. All video footage was saved in a secure Amazon S3 bucket. For the research ethics and consent process, we reviewed guidelines for installing video surveillance in the private sector as outlined by the local government, consulted with four internal sectors (corporate legal counsel, internal security team, facilities management team, and management of the employees). Then, we held a presentation session for all the affected employees to share our data collection and storage plans.

The study area is identical to the area described in the formative study, see Figure 3. From the large video dataset, we focused our attention on personal desk areas. As all of the personal desks were the same size, we could see if their configurations could be significant factors that affect behaviour. Some desks were surrounded by walls and doors, supporting a more private working space, others with only a partition. In this paper, we covered seven unique personal desk configurations. For open desk spaces, we observed five different linear desk setup variations as seen in Figure 3: (a) barrier (e.g. other desks or columns) only on one side of the desk, (b) barrier on one side, partition on the other side, (c) barriers on both sides of the desk, (d) other desks on the both sides of the desk, and (e) walls or partitions behind the desk with barriers on both sides. In addition, we included two setups where the desk was surrounded by walls or doors (Figure 3f,g). Informal collaborations within and between groups frequently occurred near their desks, especially for quick work updates, scrum meetings, urgent discussions, and small chats.

5.2 Labels used for Annotation

Based on the findings from the formative study, we defined our labels for the analysis. We included two groups of labels, ***approach type*** and ***social interaction type***. Two approach types were covered in this study: *visiting* (approach a desk while the owner is focusing on a task), and *recruiting* (approach a desk as the visitor and make eye contact with the desk owner before approaching further). In addition, inspired by Lee et al. [69] two social interaction types were covered: *discuss & chat*, and *show & tell*. In addition, we added an extra label called *eye contact* because we observed that visitors often paused in the middle of an approach until the desk owner was aware of the upcoming social interaction.

5.3 Analysis Procedure

Using the system we developed, we annotated one month of video footage using the three label groups above, as illustrated in Figure 6. We labelled *approach* when the visitor started approaching one's desk (t_0), until they started the social interaction (t_1). When the visitor started interacting with the owner, we labelled this as a social interaction until the interaction ends (t_1 - t_2). We annotate the entire duration of this interaction to visualize the weight of each position. During the moments of approach, we labelled eye-contact from where the visitor hesitates until the owner makes eye contact (t_b). The skeleton representation of ears and eyes indicates the orientation of the face, and eye contact was detected based on the assumption that when two people faced each other, they made eye contact (Figure 4c). This is a limitation of our study, but we argue that this is a reasonable assumption, especially for social interactions at personal desk areas.

Based on the annotation results, the visualization tool automatically renders aggregated heatmaps (Figure 8) and path drawings (Figure 7) according to the chosen annotated filters. These features helped us understand the overview of socio-spatial movements and patterns. We then developed the expanded heatmap and onion skinning visualizations.

Finally, we conducted brief one-on-one interviews with ten occupants to understand their intentions behind the visualized patterns that we found. This gave us more detailed insights compared to the formative study interviews as we had accurate evidence of their behaviours and we could better compare interactions or even reenact them to clarify questions about socio-spatial comfort.

5.4 Results

The resulting visualizations showed the tendency of people occupying spaces during desk visit interactions, and provide insights on socio-spatial comfort in architectural spaces. We present our findings on three behaviours: approach path, initial eye-contact, and social interactions over time.

5.4.1 Approach Path. We represent the *approach path* as a physical movement starting from the moment where a visitor appears on camera until they begin social interactions (Figure 6). We found subtle differences in approach behaviours between the situation where 'the visitor interrupts someone who is focused on working' (referred to as *visiting* for the rest of the paper), and the situation that 'the visitor was recruited by someone in the desk' (*recruiting*). When recruited, people would take an efficient and relatively linear path, as shown in Figure 7e. However, in most other cases, visitors approached while the desk owners were working along relatively curvy and long paths. For example, the visitors tended to appear from the side without invading the area behind the seated occupants (Figure 7a-d). Similarly to the findings from the formative study, interviewees mentioned that these inefficiencies in their paths, as presented in the figures, were voluntarily done to preserve social comfort. But unlike the previous study, having concrete path visualizations enabled them to provide deeper reasoning behind their behaviours.

When there were partitions on the walkable side of the desk, the end points of approach paths were relatively concentrated at one specific area (Figure 7b), which was closer to the desk compared to the partition-free setups, approx. *0.12m* from the partition (Figure 7a). On the other hand, when a column was located on the side of the desk (Figure 7c), visitors coming from that side stopped approaching near the column area (approx. *0.15m* from the column, approx. *0.3m* from the desk). The visitors commented, *"I am unconsciously led to the physical structures near the desk. I feel stable when I stay there." It seemed that the presence of partitions or columns acted as the conceptual*

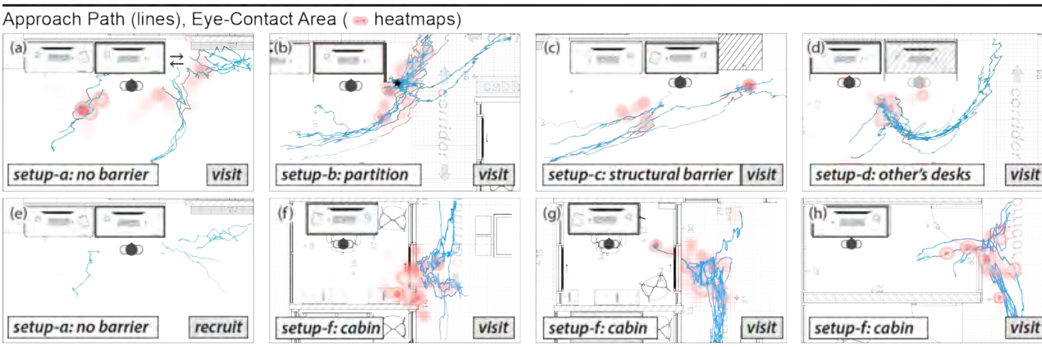

Fig. 7. Visualization of approach path (lines) and eye-contact area (heatmap) at diverse desk configurations.

destination points." Several occupants also stated those additional spatial elements were regarded as a boundary that divides personal and public zones.

In the situation where other desks were located on the other sides of the desk, the curvature of the approach paths were extreme. As depicted in Figure 7d, visitors tended to take a wide path around the nearby occupants and stopped approaching far behind them (approx. *1.3m*). From the interviews, we learned that these were were the most uncomfortable cases for visitors. One interviewee highlighted, *"I needed to find a route where the colleague I am visiting would notice me while not interrupting nearby occupants."* There were several cases where the desk owners did not notice the visitor from these distances, so, visitors approached a bit closer to get their attention but then stepped back afterwards. The occupancy of the adjacent desk did not make a clear difference in approach behaviours. The paths shown in Figure 7c&d were repeatedly shown regardless of the occupancy of the desks next to the visitee.

When personal desks spaces were divided by glass walls, occupants would occasionally enter the room and walk towards the desk area. However, the majority of the approach paths stopped outside of the room, approximately *3.3m* away from the desk (Figure 7f-h), and the visitors wandered a little while approaching. One interviewee commented, *"Wandering while approaching makes the desk owner aware of my presence. I wanted to provide some subtle notification."*

5.4.2 Eye-Contact Area. We also annotated the moment when visitors made *eye contact* with the desk owner to ensure they would be aware of the upcoming social interactions. From the distribution of footsteps on the path, we noticed that visitors slowed down in the middle of their approach until making eye-contact. Collected eye-contact positions were visualized as a heatmap in a pink colour in Figure 7. In general, interviews conveyed that the area between the desk owner and the eye contact spot represents the area regarded as a personal zone. (e.g., *"I unconsciously stopped my approach when I approached an area that I felt needed my colleague's approval to enter.. Eye-contact was one of the nonverbal communications to confirm this."*)

In open desk setups, when a side of the desk was empty (Figure 7a,b,c), the eye-contact zones were usually located at that side of the desk, and there were no significant differences for the location of the eye-contact zone with respect to nearby architectural elements, such as columns. However, the partitions contributed to bringing eye-contact zones closer to the desk. By tracking back the full skeleton pose data of those moments together with interview results, we found the reason was the visual obstruction, not the psychological aspect of the partition. But when other occupants were sitting nearby, the eye-contact zone is located far behind the occupants (Figure 7d).

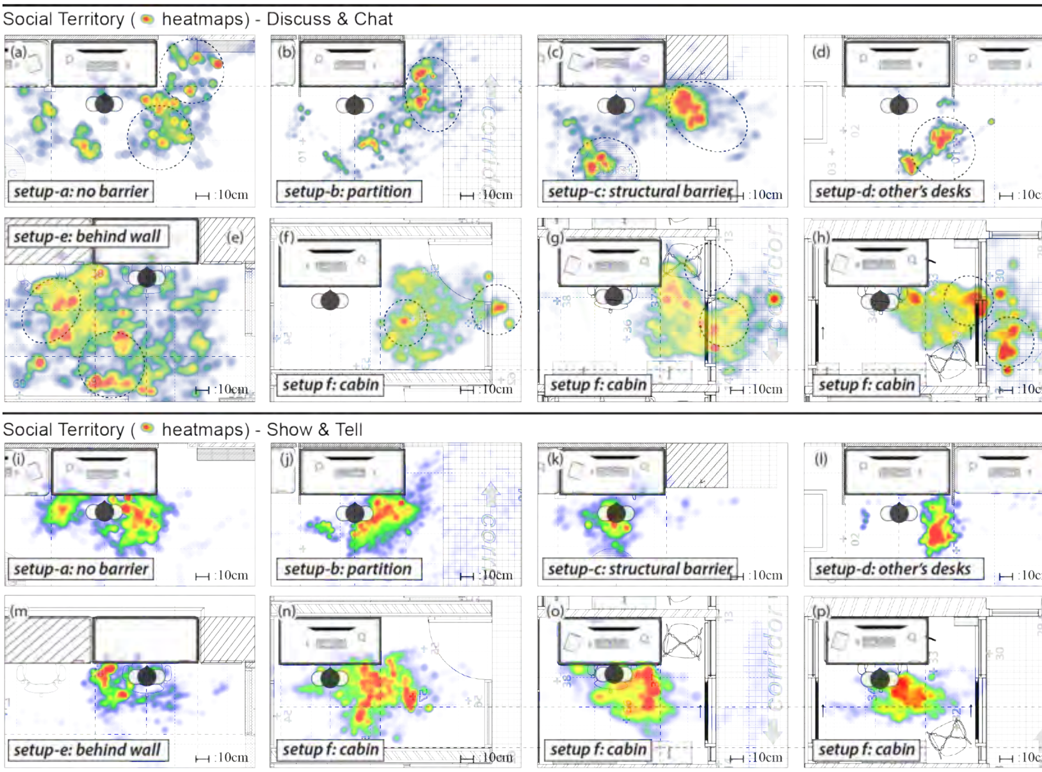

Fig. 8. Visualization of approach path (lines) and eye-contact area (heatmap) at diverse desk configurations.

Desk owners looked back and made eye contact with visitors even though visitors were not within their visible range. Four interviews highlighted that the desk owners who are surrounded by other desks constantly pay additional attention to the area behind them by catching sounds or light changes to be ready for upcoming interactions. This provided us insight that eye-contact zones can be also interpreted as an invisible boundary between social and personal zones. This finding was aligned with a few cases of false-positive moments where the desk owners looked back when people were passing by too close to them.

At cabin style personal desks, the eye-contact area is widely distributed along the glass wall (Figure 7f-h). This effect may be related to the wandering behaviour of visitors around the door area until capturing the owner's attention. This showed that although the primary purpose of a wall is to help occupants concentrate on their work, a glass wall can also be distracting from the presence of people at further distances.

5.4.3 Social Territory Over Time. The *social territory* defines the area that the visitor occupied during the social interaction (Figure 2 right). Visitors changed their positions over time throughout the interaction, and their entire occupied social territory seemed to be dependent on spatial layouts, visually confirming the findings from the formative study. As the owners of the desks are mostly seated, standing visitors have a lower *proxemic gravity* [61] and more frequently re-position themselves. Although the interviews from our previous formative study showed that visitors were not aware of their minor movements, the heatmap visualization helps us understand the space that visitors occupied the most over time as well as how they moved around (Figure 8).

We found a significant difference in social territories between discuss & chat interactions and show & tell interactions, similar to the findings from ethnographic approaches [69] (Figure 8i-p). The results identified closer social distances when compared to Hall's social proxemics theory [46]. Whereas surrounding walls increased the distance about 0.88m, the aggregate territory sizes were found to be almost identical regardless of spatial settings. On the other hand, social territories during the discussions were widely distributed when there was empty space near the desk (Figure 8a) or when another desk was located next to the target desk (Figure 8e). The interviews revealed that this was because the neighbouring desk was not in use, and therefore regarded as empty space. The empty space near the desk provided visitors with much more socio-spatial freedom; still, the most frequently occupied area remained far beyond the side of the desk.

Some desk configurations produced more concentrated social territories. When there were partitions (Figure 8b) or columns (Figure 8c), visitors tended to locate near those elements (<0.9m). These two cases were where the distance between the visitors and desk owners were the smallest throughout our study. Furthermore, when other occupants were sitting at nearby desks (Figure 8d), social territories converged towards the area behind the desks. Different from the approach interaction, visitors did not cross the implicit boundary between two desks, and kept a closer distance with the target desk owner than other occupants. The visitors highlighted, *"I am eager to give a clear impression that I am there to communicate only with that specific person (my target visittee)."*

In cabin style desk setups, the entire space between the desk owner and the glass wall were actively used during discussions. However, social territories were especially concentrated outside of the cabin, even though the social-spatial distance was farther than most other observed interactions (Figure 8f-h). According to our observations, visitors also tended to move towards the wall as discussions ran longer, making this area also a frequently used position. However, in this office layout design, the outside of the glass wall was not considered as the space needed for the person inside, but rather was considered to be part of the corridor. Therefore, we observed a few moments where the visitors and other passersby bumped into each other and created a slight bottleneck.

6 DISCUSSION

Embodied interactions contain rich cognitive information on how we experience built environments or technologies [27, 71]. Consequently, they have the potential to answer design problems in HCI and Architectural studies [42]. In this section, we define and discuss socio-spatial comfort and how this concept is differentiated from current theories. We reflect on our methodological approach and analysis system and discuss the potential uses of vision-based analysis for future designers and researchers. In addition, we discuss the implications of socio-spatial comfort for shaping user-centred human building interactions: focusing on computational architectural design tools and intelligent physical environments. Lastly, we discuss the limitations of our study and future work.

6.1 Socio-Spatial Comfort in Human Building Interaction

Krogh et al. [61] proposed the concept of *socio-spatial literacy* to describe physical space-dependent social behaviours (e.g., groups leaning towards the camera during the conference call, poses gravitating towards workstations, etc.). Inspired by this work, we proposed a set of concepts called *socio-spatial comfort*: social buffer, privacy buffer, and varying proxemics (Figure 11). Krogh's work focused on describing how technology or physical objects influence flexibility in socio-spatial transitions. Instead, our focus is to conceptualize how the occupant's adjust their micro-movements to increase social comfort and how social territories may be formed.

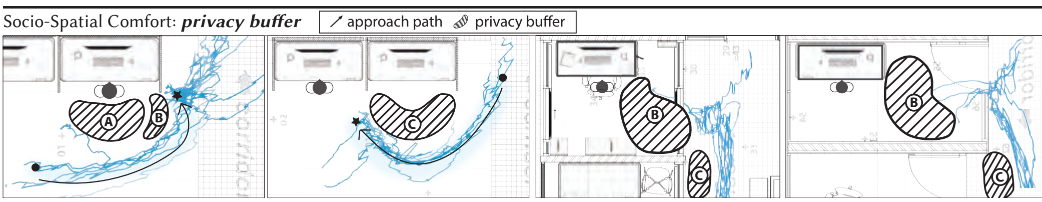

Fig. 9. *Privacy Buffer* explains how and why the visitors tend to avoid an area with a goal of improving social comfort when approaching others' desks.

6.1.1 Privacy Buffer. The visualization results showed that when people approach a coworker's desk, there were areas that people tend to *avoid* passing through, making their approach path different from an optimal path (Figure 2 left, green zones). We named these areas *"privacy buffers"*, and different buffer shapes at each desk layout are illustrated in Figure 9. Identified privacy buffer zones can be categorized into three types.

The first type of privacy buffer occurred to not invade *personal space* [96] during informal desk interactions, as shown in Figure 9, zone B. We draw a shape boundary from aggregated path visualizations by repeatedly detecting a distance between the position of a desk owner and the final position of the approach path. This can be explained as a type of *territoriality* [7] and *personal space* [96] which describes an invisible personal boundary that is influenced by perceptions of comfort and privacy. However, whereas personal territoriality has been described as simple physical distances [46], we propose that it can be explained as shapes which are dependent on space configurations. Second, *privacy buffers* also emerged when visitors were trying to avoid interrupting other people who are not the intended desk owner. For example, as depicted in Figure 9, second image, the occupants took a longer route to visit the person at the left desk when another desk was located nearby. We observed that their approach paths are just out of the eye-contact zones of other desks (Figure 7). In the future, this type of personal space [96] buffer zone can be estimated from the neighbouring desk's eye contact zones. Third, another reason for the *privacy buffer* was to provide a social impression that *"I am respecting your personal privacy"* especially in personal desk setups. An example would be the area immediately behind the occupants (or desks), as shown in Figure 9, zone A. This concept is related to *visual exposure* from the desk owner's perspective as shown in Alavi's work [4].

In HBI and architectural design, *"privacy"* in social comfort has been investigated primarily in terms of *visibility* [94]. Using 3D isovists, several methods (e.g., space syntax) evaluated the visual exposure of one's area from external spaces or people [4, 14]. However, our findings about the *privacy buffer* indicates that the term *privacy* needs to be considered not only with respect to vision (Figure 9, zone A), but also to spatial territory (Figure 9, zones A,B). In addition, whereas personal space [7, 96] has been defined from the first-person perspective, our study showed the importance of considering the 3rd-person perspective when designing for socio-spatial comfort (how visitors perceive my personal space).

6.1.2 Social Buffer. The collected approach paths do not illustrate the area that occupants want to *avoid*, but want to *pass by*, or stay at for a moment before initiating the social interaction. We call these zones a *social buffer*, as illustrated in Figure 10. Social buffers contribute to shaping comfortable social interactions at personal desk areas by not startling the desk owners, and allowing them to smoothly engage in social interaction with visitors. The visitors appearing from the side of the desk owner is evidence for the existence of a social buffer. We found that the social buffer

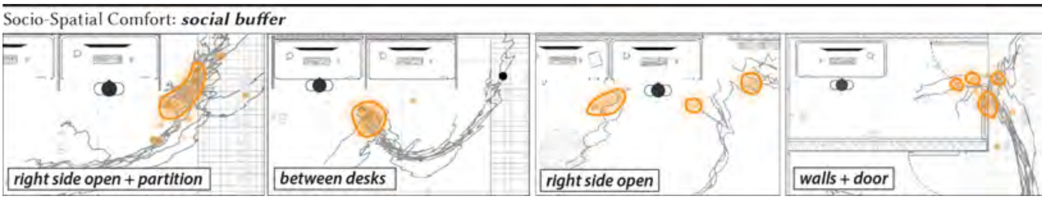

Fig. 10. *Social Buffer* explains how and why visitors tend to pass by and stay within a certain area to smoothly engage others during social interactions.

is related to the eye-contact zone generated from our heatmap visualization, and a slower speed along the approach path.

In social computing, *attention* has been introduced as a concept that mediates awareness and privacy for both collocated and virtual collaboration [15, 48, 92]. Birnholtz [15] highlighted that paying attention to someone is an implicit request for interaction. The social buffer builds upon this theory by describing spatial aspects of *attention* and *awareness*. We found that the distribution of social buffers varied based on the desk setups, and where notably different from *visibility graphs* which describe the area directly visible from a given location [102]. Rather, a social buffer is a type of tacit knowledge [84] regarding the area perceived to be "the area that my visitor will pass by".

Our findings support related work suggesting that informal collaborations enhance work creativity and communications [5, 18, 61, 89]. Although there have been several studies that discuss the potential conflicts between work productivity and communications [24, 99], socio-spatial comfort may integrate the concept of personal privacy and work interruptions. For example, social buffers minimize work interruptions when passing visitors try not to invade the visibility areas of the surrounding occupants. Furthermore, partitions installed to increase productivity were also found to enhance social comfort by providing implicit social territories.

6.1.3 Varying Proxemics. Early work on proxemics [46] described *static* distances. However, we found that preferred social distances, during collocated desk visits, are dynamic and highly depend on the space layout and involved devices (e.g., monitor).

The proxemic distance can be varied due to several factors, such as the presence of other people who are not involved in the social interaction (Figure 11, 2nd image), and the spatial elements (Figure 11, 1st, 2nd, 4th image). For example, the comfortable proxemic distance becomes farther when the desk is located in between the other desks (e.g., Figure 8-d). Several works have studied wall display interactions taking into account distances between people and walls, but the entire

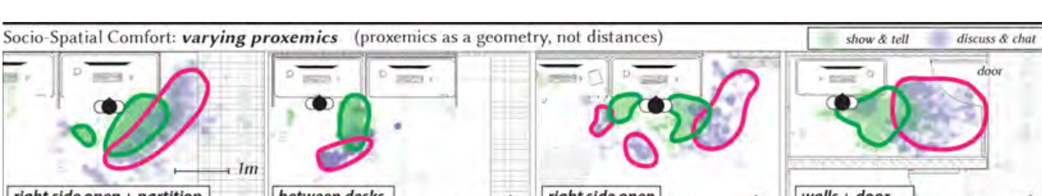

Fig. 11. A convex hull visualizes the *proxemics* as geometry rather than a distance, which is dynamic and depends on space layout.

ecology of environment (furniture, wall, physical layouts) was not considered. Our concept extends existing theories by providing evidence of more complex proxemics in the accompanying dataset.

Going beyond static formations and distances [69, 74], the concept of varying proxemics highlights the need to represent and interpret dynamic phenomena. Previously, Gronbaek et al. [38] extended the notion of proxemic theory with temporal aspects and introduced the concept of *proxemic transitions* (*transition speed*, *stepwise reconfiguration*, and *radical shifts*) to support collaboration dynamics. However, our longitudinal study also showed the importance of continuous movement during social interactions in terms of preserving comfort, and we propose a representation of these variations.

6.2 Socio-Spatial Comfort for Designing User-Centred Environments

Our findings revealed that socio-spatial comfort is driven by a varied set of factors, from spatial layouts to computing devices. Moreover, the notion of *proxemic interactions* [12, 37] seeks to operationalize users' spatial arrangements to become a means of interacting with technology. However, our computing devices and displays can also be considered to be part of the built environment. Prior work on designing or configuring shared devices has been focused on the interactions between the devices and users, or between social groups [10, 73, 100]. For example, proxemic distances with a large display [10, 105] or social formations [100] have been the focus. We argue that architectural space and furniture need to be considered as a whole set to understand and accommodate socio-spatial comfort.

Our work could help architects or interior designers make design choices by making comfortable social zones more explicit on the 2D layout. For example, the concepts of "social buffer" and "privacy buffer" along with different workspace configurations can help inform the layout and positioning of elements in offices so as to avoid any unnecessary obstructions and use elements such as partitions and walls in better ways towards comfort. Especially, bringing forward the *social buffer* zones in the design process could contribute to making the design both socially friendly and efficient. We found that social buffers play a functional role where people can increase comfort by getting *attention* and *awareness* [15]. However, despite the fact that social buffers are concentrated around the walls and doors of a cabin office (Figure 8-f,g,h), the interior designers originally planned that area as a hallway, which leads to congestion between visitors and occupants travelling by. We expect this socio-spatial comfort visualization could help designers look at spaces not only with an object-centric perspective, but with a user-centred perspective as well.

In addition, our socio-spatial comfort concept could suggest new perspectives of looking at social distancing rules as with the COVID-19 pandemic. To minimize the viral transmission in shared spaces, social distancing rules (for example, keeping 2.0m of interpersonal distance) has been applied in various contexts. In offices, an approach being applied now is drawing a *2-meter* radius circle near the desk to avoid re-configuring desks [87]. As cultural norms change, sometimes drastically, these socio-spatial concepts may also be dramatically different.

6.3 Socio-Spatial Comfort for Computational Design Systems

Traditionally, Computer-Aided Design (CAD) systems tried several techniques to systematically demonstrate intended or expected user experiences with a building model. Space Syntax is a representative example that quantitatively analyzes spatial aspects of human experiences and puts them into a digital architectural model. However, our study revealed that *socio-spatial comfort* is highly related to perceptional aspects, which are difficult to quantify. For example, *privacy buffer* is not only about the visibility graph but also the perceptional interpretation of personal territoriality. A data-driven approach has been addressed to bring this rich qualitative knowledge into computational systems [55, 88]. We believe that our *socio-spatial comfort* concept with a longitudinal footstep dataset contributes as a foundational resource to inform human-centered computational design tools. We see the potentials in using these as analytic tools (simulation) as well as generative instruments in the architectural design process.

In architectural planning, *simulation* has been widely applied to evaluate user-driven scenarios in buildings [8, 36, 43, 52, 91]. Most of them use traditional path-finding algorithms (A* [47] or Dijkstra's [25]) aligning with pre-assigned schedules or scenarios (work schedule, or emergency egress scenarios). However, our work indicates that socio-spatial comfort influenced people to approach others along paths that were not optimal, and identified the privacy buffer and social buffer patterns that shape a comfortable path. In the future, taking a similar approach as SmartManikin [68], we expect socio-spatial comfort can be used to simulate virtual human models based on comfort. This could extend the current stream of simulation-driven design optimization and generation [31, 78] by bringing user's perceptions into the systematic process (e.g., how the privacy buffer interferes with travel efficiency).

6.4 Socio-Spatial Comfort as Intersection between HBI and HRI

In Human-Robot Interaction (HRI), social robots have been introduced in various contexts, such as a shopping assistant [39], a moving garbage can [112], and a telepresence avatar [2, 41, 98]. As these robots were intended to perform tasks on behalf of humans, robot interactions were designed to perform socially comfortable and appropriate behaviours. For decades, a large body of work looked at social theories or social norms to design a friendly way of patrolling or configuring the robots, concerning spatial presence as well as behavioural interactions [1, 29, 53, 76, 77]. For example, wiggling interactions were suggested for moving garbage cans to get people's attention, and the approach model for admonishing events were suggested to demonstrate realistic movements.

However, our study showed that the spatial zones that social robots should avoid or pass by are dependent on the physical layouts of the environment. We believe that our concept of *socio-spatial comfort* could contribute to designing comfortable social navigation or arrangements by providing an additional layer of information to the physical spaces based on the perceptional aspect. Our concept can also provide dynamics for the spatial movements of telepresence robots, which were static in prior works [66, 111], using the dataset from a *varying proxemics* aspect, to provide more realistic social experiences.

6.5 Vision-Based Space Analysis System for User-Centered HBI and Architecture

In this paper, we proposed a vision-based micro-space occupancy analysis system to efficiently analyze the patterns of physical body movements in relation to spatial constraints. We showed that a computer-vision approach could provide evidence of people's patterns, which have the potential to be used as interview support as well as computational analysis for design systems. We successfully captured repeated patterns from the first two weeks of data and confirmed these patterns from an additional two weeks of data. While one month of observation was performed in this study, we recommend that future researchers repeat the cycle of data capture and analysis with a short time period until repeating patterns are found. In this subsection, we reflect on our methodological approach and discuss its potential for future projects.

First, our system could successfully reproduce people's physical movements from a large dataset of video recordings collected in-the-wild. Calculating the micro-spatial positions using skeletonized video footage enabled us to collect real-world data in a natural setting (without the need for wearable sensors) on a large scale. We believe that our approach made significant efforts to understand what privacy may mean in shared workspaces. This ethical human-centred approach in today's world of sensor-rich environments can exemplify the benefits of automated data collection methods while preserving privacy. However, although the camera footage we used for the analysis was anonymized, the raw video footage needed to be saved and stored until the skeletonization process was complete, which led to privacy concerns from some of the employees. Future work needs to explore how to run the skeletonization in real-time and only save the anonymized version of the data.

Second, different from previous analysis tools [20, 69], automatic skeleton tracking and 2D position projections were found to be useful for our in-depth socio-spatial analysis. This enabled us to filter and categorize the patterns for a particular person (e.g., a visitor's path) or a particular area (e.g., the social territory of a specific desk). Our tool can be applicable to other contexts by using the video footage. In this paper, we used video captured by RaspberryPi cameras to have full control over the data processing and to customize functionality such as motion compression; however, videos captured from other cameras can also go through our data processing pipeline and generate the outputs as we presented in this paper. In the future, this feature could be especially useful when researchers want to quickly test assumptions and want to cluster behaviours from large video datasets.

Third, in terms of visualization, the system enabled us to smoothly iterate between four different aspects (Figure 5), which provided a broad spectrum of insights from 'overview' to 'single instance,' and from 'physical movements' to 'embodied aspects.' The traditional heatmap technique was helpful to understand which areas were preferred in each desk setup from a longitudinal dataset, and the aggregated paths provided micro-details on how visitors approached one's desks. Different from previous spatial analysis tools for social studies, focused on 2D representations of 2D footsteps [20, 91, 105], we combine these approaches with spatial-temporal visualization techniques often used in geography [57, 82]. The layered heatmap and onion skinning methods provided additional depth to our data interpretation by explicitly showing temporal dynamics in socio-spatial behaviours. However, the limitation with our current interface was the difficulty in transitioning between aggregated patterns (heatmap style) and single instance visualization (pose onion skinning or path drawing). In the future, the real-time synchronization between each visualization could increase efficiency in data analysis.

Lastly, our vision-based system provided real-world evidence of people's socio-spatial patterns and helped us to interpret interview materials. Compared to using hand-made sketches as interview sources (as in our formative study), the computationally visualized patterns decrease the researcher's time for manually clustering the observed patterns and engaged interviewees to better self-reflect on their behaviours. In addition to interviews, the visualization output itself made it easier for researchers to compare the data between single instances as well as between different desk layouts. In this manner, we believe that our system could promote the concept of *integrated workflows* [42] of the architectural design process proposed by Gulay et al. in the HCI community. They argued that the current digital architecture models do not adequately provide fundamental cognitive resources yet, and the fluid feedback loop between digital and physical realms could tackle the limitations of current digital design workflows. Our tool can help improve the current practice of understanding space usage and can support designers and architects to understand the embodied way of using physical space.

6.6 Study Limitations & Future Work

Our research has several limitations. First, we collected occupants' behaviours as skeletonized figures. Contextual information such as sounds (e.g., simple decibel levels, attention level, or content) or occupant types (e.g., manager, employee) was not collected in our study. However, if this additional information can be captured together in the future, we can correlate the embodied interactions with other streams of sensor data, such as sound, temperature, light, etc. to investigate deeper interrelationships.

We investigated socio-spatial comfort by observing informal desk visiting interactions at a specific office. Due to the variation in project sizes and collaborator locations, the interactions between colleagues with desks right next to each other were not frequent and ignored from the analysis. In the future, more varied contexts need to be considered to attempt to generalize these concepts. Still, we argue that *socio-spatial comfort* could also be useful in other physical spaces that causes multiple transitions between social interactions and individual tasks; for example, hospital offices or public infrastructures such as information reception, places with unmanned information kiosks, or community environments.

Furthermore, additional techniques need to be applied to further analyze and visualize socio-spatial behaviours. As our primary focus of this paper was to look at the frequency and transitions, we focused on visualizing the overview of spatial occupancy patterns. However, similar to the study of Gronbaek et al. [38], we found the speed of the behavioural transitions to be one of the important factors in social behaviours. Because the speed and acceleration of people's approach behaviours can be currently inferred by the distances between footsteps in the path, we could uncover subtleties in approach style. The future work could apply advanced analysis techniques to calculate the speed of the skeleton's movements or the orientation of the face to provide another layer of embodied information. Also, adding skeleton-based activity recognition could help correlate between important social behaviours (e.g., waving hands for getting attention) and spatial aspects. In addition, we could analyze the relationship between space layout and the shape of the buffer zones using the footsteps.

Finally, we found that *socio-spatial comfort* is a type of embodied knowledge and we examined this concept by collecting dynamic physical movements from the video. Our interview results confirmed our methodological approach; however, the detail level of comfort at each physical location was ignored. To capture these subtle differences, future studies need to explicitly measure the comfort level at selected highlighted spots, perhaps with a participatory sensing method [108].

7 CONCLUSION

This paper made an attempt to understand *socio-spatial comfort* with respect to spatial layouts in order to bridge the notion of social computing and human building interactions with a user-centered perspective, focusing on informal collaborations at personal desks. Our preliminary study revealed that *socio-spatial comfort* is a type of *tacit knowledge* which can be captured by collecting and finding patterns from people's embodied interactions in-the-wild. Therefore, we proposed a vision-based analysis method to systematically capture the micro-physical movements of people who socially occupy the space over time, and visualize the outputs with different levels of focus (aggregated overview, temporal overview, path overview, and pose overview). By aligning the findings with interview results, we found that the occupant's behaviours while approaching and interacting with people are not based on efficiency but vary at each desk configuration due to diverse aspects of social perceptions. These insights have driven our theoretical concept of *socio-spatial comfort* (*social buffer*, *privacy buffer*, and *varying proxemics*) to illustrate how the dynamic movements in the physical space can contribute to comfortable social interaction experiences. We argue that socio-spatial comfort can not be estimated simply by visibility-oriented privacy metrics [15], social territoriality [7, 96] or static proxemic distance [46]; rather it is based on the co-relational mapping between human social perceptions and micro spatial zones, which can be derived from real-world data. We believe that socio-spatial comfort could be an essential concept in designing comfortable experiences for human building interactions. Understanding the key factors of these experiences can also support the adaptation of space layouts as well as designing pervasive environments, including intelligent objects (displays) and telepresence robots.

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A APPENDIX

A.1 Signage for Data Capturing

For awareness of the occupants about data collection, we attached a sign as shown in Figure 12 nearby each camera. The signages were designed based on the preliminary chat with the occupants in the office. Based on understanding their primary concerns regarding vision privacy, we included information about the data collection period, the position of the camera, range view of the camera, and how the data will be stored (what the researcher would see). We linked to a website address to provide detailed information for those who want to know more.

A.2 Ethics for Data Collection

To collect video data of occupants in a private company, we went through the research ethics procedure as shown in Figure 13. After reviewing the guidelines from the Government of Canada for operating surveillance cameras, we consulted with four internal sectors within the company. Then, we gave a presentation to the employees to share our research goal as well as the data collection details (time period, camera locations, data storage transparency). The entire process took about a month to complete.

A.3 Socio-Spatial Dataset

We share the dataset that we used in this paper as supplementary material. The dataset is composed of JSON files (clusters of 2D footprints) and PNG files (images of 2D floor plans). The coordinates for the footprints are based on the image's pixels and all the images share the same scale ($1px = 0.348cm$), as shown in Figure 14-bottom. Each JSON file includes timestamp, x-coordinate, y-coordinate, and the skeleton ID. The name of the JSON files consists of the *desk code* and the *data type*, as depicted in Figure 14-top.

Fig. 12. Sample signage that was placed at the entrance of recorded areas.

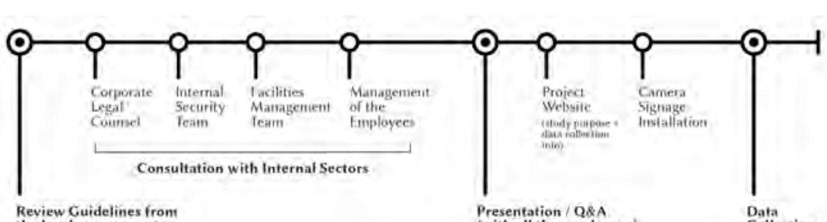

Fig. 13. Ethical procedure for our data collection.

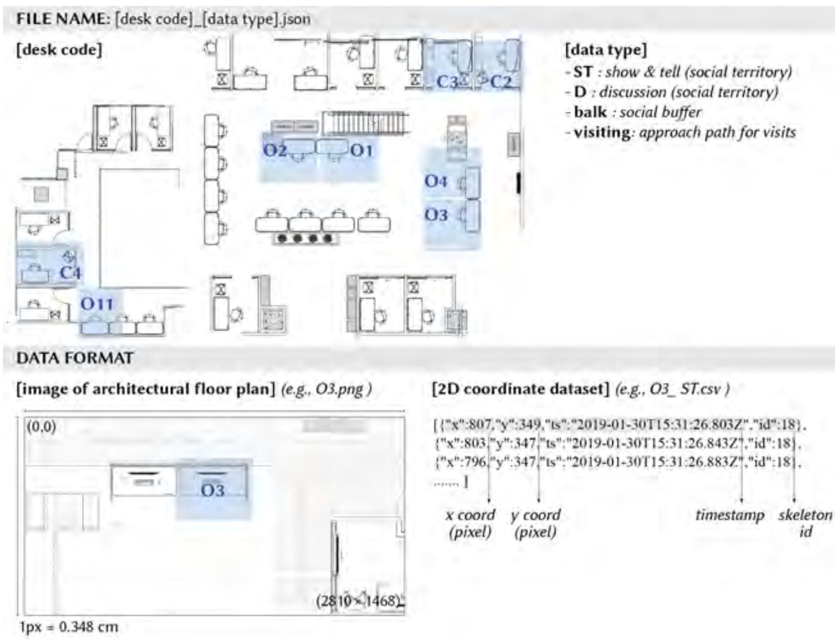

Fig. 14. The structure of the dataset we shared with this paper.